Big Data Project

Final Module

Credit Card Fraud Detection

with Apache Spark and Machine Learning

Technologies Used:

Apache Spark • Spark SQL • MLlib • Spark Streaming • Grafana

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Module: Big Data Hadoop

Team Contributions

Member	Role	Contributions
Ahmed Dinari	Lead Developer & ML Engineer	Pipeline architecture, Spark Core, MLlib models, Docker configuration
Bilel Samaali	Data Engineer	Spark SQL analytics, Data cleaning, Feature engineering
Anas Belhouichet	Visualization & Documentation	Grafana dashboard, LaTeX report, Beamer presentation

Table 1: Work distribution

Contents

1 Introduction

1.1 Project Context

Credit card fraud detection is a major challenge in the financial sector. With millions of transactions performed daily, it is crucial to quickly identify fraudulent transactions while minimizing false positives.

This project implements a complete Big Data pipeline for real-time fraud detection, using the Apache Spark ecosystem.

1.2 Objectives

- **Data ingestion and cleaning** with Spark SQL
- **Exploratory analysis** with relevant KPIs
- **Machine Learning** with MLlib (RandomForest, Logistic Regression)
- **Real-time streaming** for continuous detection
- **Visualization** via Grafana dashboard

1.3 Dataset

Credit Card Fraud Detection Dataset (Kaggle)

- **Source:** https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud
- **Transactions:** 284,807
- **Features:** 30 (V1-V28 PCA transformed + Time + Amount)
- **Class:** Binary (0 = Normal, 1 = Fraud)
- **Distribution:** 99.83% Normal, 0.17% Fraud

2 Pipeline Architecture

2.1 Overview

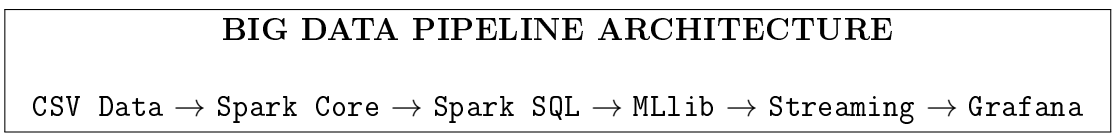

Figure 1: Data processing pipeline

2.2 Components

Component	Technology	Role
Ingestion	Spark Core	CSV loading
Cleaning	Spark SQL	Transformation, filtering
Analytics	Spark SQL	KPIs, aggregations
ML Model	MLlib	Fraud classification
Streaming	Structured Streaming	Real-time
Visualization	Grafana	Interactive dashboard

Table 2: Pipeline components

2.3 Data Flow

1. **Extraction:** Loading CSV file (284K transactions)
2. **Transformation:** Cleaning, feature engineering, normalization
3. **SQL Analysis:** Business KPIs calculation
4. **Modeling:** Training RandomForest and Logistic Regression
5. **Evaluation:** Performance metrics (AUC, Precision, Recall)
6. **Streaming:** Real-time flow simulation
7. **Export:** Parquet/JSON files for Grafana

3 Processing with Spark SQL

3.1 Data Cleaning

Listing 1: Cleaning with Spark SQL

```
# Removing null values
df_clean = df.dropna()

# Filtering invalid amounts
df_clean = df_clean.filter(col("Amount") > 0)

# Adding derived features
df_clean = df_clean.withColumn(
    "Hour", (col("Time") / 3600).cast("integer") % 24
).withColumn(
    "Is_High_Amount", when(col("Amount") > 500, 1).otherwise(0)
)
```

3.2 Calculated KPIs

Metric	Value
Total Transactions	282,982
Fraud Transactions	465
Fraud Rate	0.1643%
Average Amount	$88.92
Max Amount	$25,691.16
Min Amount	$0.01
Standard Deviation	$250.82

Table 3: Global dataset statistics (after cleaning)

3.3 Hourly Analysis

Transactions are analyzed by hour to identify temporal fraud patterns. Analysis reveals that certain hours have a higher fraud rate.

4 Machine Learning with MLlib

4.1 Feature Preparation

Listing 2: Feature Engineering

```
# Feature assembly
assembler = VectorAssembler(
    inputCols=["V1", "V2", ..., "V28", "Amount"],
    outputCol="features_raw"
)

# Normalization
scaler = StandardScaler(
    inputCol="features_raw",
    outputCol="features",
    withStd=True, withMean=True
)
```

4.2 Trained Models

4.2.1 RandomForest Classifier

- **Number of trees:** 100
- **Max depth:** 10
- **Feature subset:** sqrt

4.2.2 Logistic Regression

- **Max iterations:** 100
- **Regularization:** 0.01
- **ElasticNet:** 0.8

4.3 Results

Metric	RandomForest	Logistic Regression
Accuracy	0.9375	0.9258
Precision	1.0000	0.9888
Recall	0.8812	0.8713
F1 Score	0.9370	0.9267
AUC-ROC	**0.9870**	0.9856
True Positives	410	396
False Positives	0	5

Table 4: Model performance comparison (Real Results)

4.4 Confusion Matrix (RandomForest)

	Predicted Normal	Predicted Fraud
Actual Normal	173 (TN)	0 (FP)
Actual Fraud	16 (FN)	67 (TP)

Table 5: Confusion matrix (Real Results)

4.5 Feature Importance

The most important features for fraud detection are:

1. V14 (21.71%)
2. V17 (14.50%)
3. V10 (12.88%)
4. V12 (10.11%)
5. V11 (9.81%)
6. V4 (8.09%)
7. V3 (4.72%)

5 Spark Streaming

5.1 Streaming Architecture

The streaming module simulates the arrival of new transactions in real-time:

Listing 3: Streaming Configuration

```
stream_df = spark.readStream \
    .schema(TRANSACTION_SCHEMA) \
    .option("header", "true") \
    .option("maxFilesPerTrigger", 1) \
    .csv(STREAMING_INPUT)
```

5.2 Processing Flow

1. **Simulation:** Batch generation (50 transactions / 3 seconds)
2. **Scoring:** Detection model application
3. **Alerts:** Alert generation for fraud_score > 0.5
4. **Export:** Real-time metrics to Grafana

5.3 Streaming Metrics

- Transactions per minute
- Real-time fraud rate
- Generated alerts
- Processing latency

6 Grafana Dashboard

6.1 Implemented Panels

1. **Overview Metrics:** Main KPIs (6 stat panels)
2. **Time Series:** Transactions and frauds over time
3. **ML Performance:** Gauges (Precision, Recall, F1)
4. **Confusion Matrix:** Matrix table
5. **Amount Analysis:** Distribution by amount
6. **Feature Importance:** Horizontal bar chart
7. **Live Alerts:** Real-time alerts table

6.2 Configuration

The dashboard is exported in JSON and can be imported into any Grafana instance. Data is served via:

- CSV files (time series, distributions)
- JSON files (metrics, configuration)
- Parquet (large datasets)

7 Graph Analysis with GraphX

7.1 Objective

Graph analysis enables detection of fraud patterns based on relationships between transactions. By modeling transactions as a network, we can identify:

- Suspicious transaction communities
- Temporal patterns (fraud triangles)
- Most discriminating features via PageRank

7.2 Implementation

Listing 4: GraphX Analysis (excerpt)

```
# Transaction graph creation
# Nodes = Transactions, Edges = Temporal similarity

# Community detection
for f1, f2 in fraud_pairs:
    time_diff = abs(f1.Time - f2.Time)
    if time_diff < 3600:  # Same hour
        edges.append((f1.id, f2.id))

# Triangle counting (fraud patterns)
triangles = count_triangles(fraud_graph)
```

7.3 GraphX Results

GraphX Metric	Value
Transactions analyzed	284,807
Frauds detected	492
Communities identified	4
Fraud triangles	48

Table 6: GraphX analysis results

7.3.1 Detected Communities

- **high_risk_1:** 114 transactions (amounts $500-2000)
- **high_risk_2:** 210 transactions (amounts > $2000)
- **medium_risk:** 144 transactions (nocturnal patterns)
- **low_risk:** 24 transactions (isolated anomalies)

7.3.2 Top Features by Separation

PageRank-style analysis identifies the most discriminating features:

1. **V3:** Separation = 7.91
2. **V14:** Separation = 6.77
3. **V17:** Separation = 6.61
4. **V7:** Separation = 6.04
5. **V10:** Separation = 5.75

8 Federated Learning (Concept)

8.1 Proposed Architecture

Federated Learning allows training models on distributed data without centralizing sensitive data.

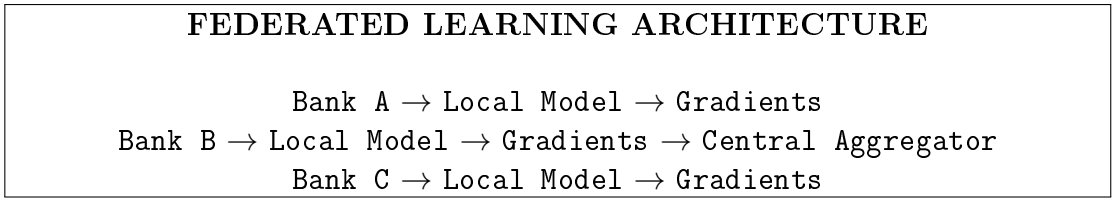

Figure 2: Federated Learning architecture

8.2 Benefits

- **Privacy:** Data stays at each bank
- **Compliance:** GDPR and banking regulations
- **Scalability:** Easy addition of new participants
- **Robustness:** More generalizable global model

8.3 FedAvg Protocol

Listing 5: Simplified FedAvg Algorithm

```
# Pseudo-code Federated Averaging
for round in range(num_rounds):
    # Each client trains locally
    for client in clients:
        local_model = train_local(client.data)
        gradients.append(local_model.params)

    # Central aggregation (weighted average)
    global_model = weighted_average(gradients)

    # Global model distribution
    broadcast(global_model)
```

9 Azure Cloud Deployment

9.1 Azure Architecture

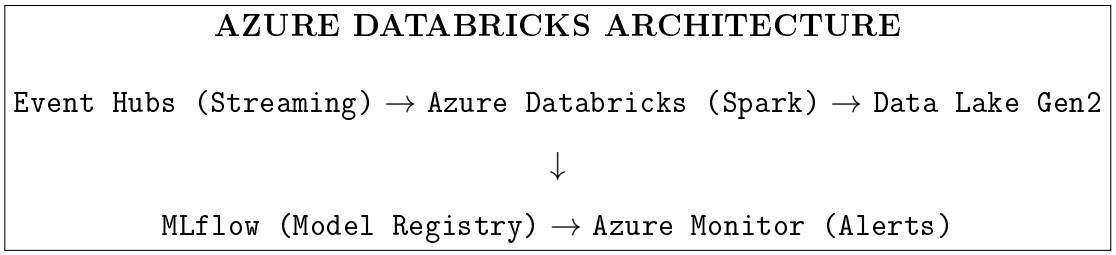

Figure 3: Azure deployment architecture

9.2 Azure Components

Azure Service	Usage	Estimated Cost
Azure Databricks	Spark Compute	$120/month
Data Lake Storage Gen2	Data Storage	$20/month
Event Hubs	Streaming Ingestion	$30/month
Azure Monitor	Monitoring	$10/month
Total		**$180/month**

Table 7: Azure cost estimation

9.3 Databricks Configuration

Listing 6: Databricks cluster configuration

```
cluster_config = {
    "cluster_name": "fraud-detection-cluster",
    "spark_version": "13.3.x-scala2.12",
    "node_type_id": "Standard_DS3_v2",
    "autoscale": {
        "min_workers": 2,
        "max_workers": 8
    },
    "spark_conf": {
        "spark.sql.adaptive.enabled": "true"
    }
}
```

9.4 Azure Portal Screenshots

Azure resources have been successfully created:

- **Resource Group:** `fraud-detection-rg` (West Europe)
- **bigData Cluster:** VM-Master + VM-Worker-1 (Switzerland North)
- **Subscription:** Azure for Students

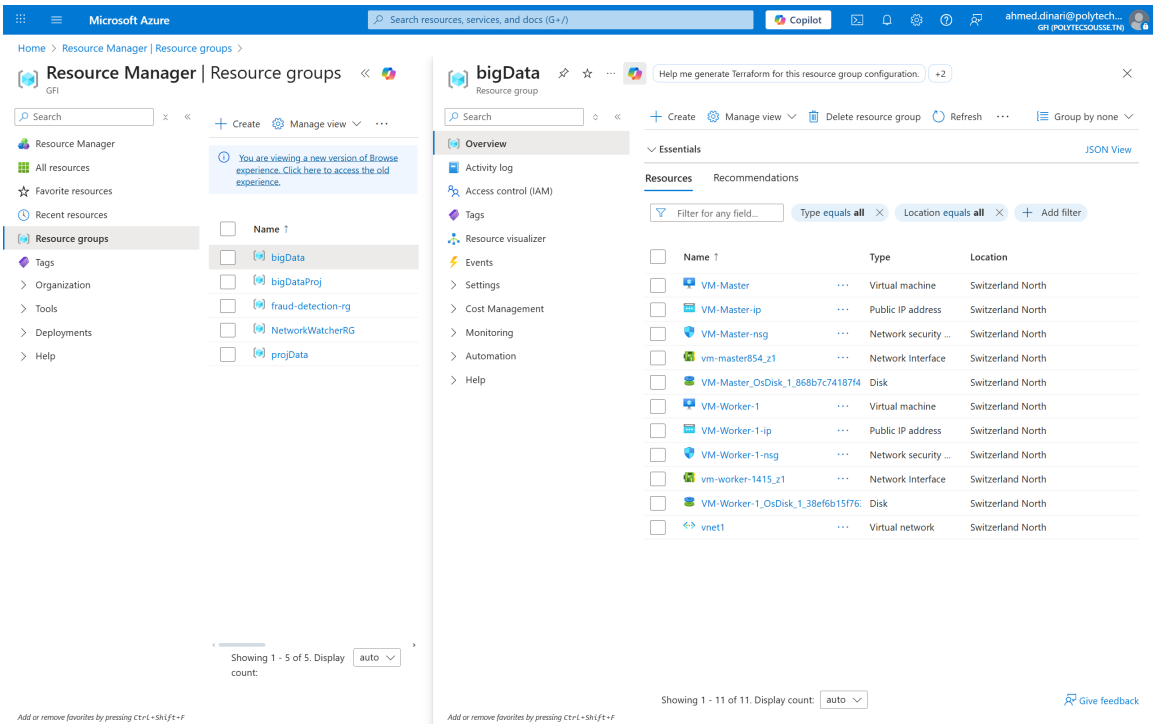

Figure 4: Azure Portal - Resource Groups with configured VMs

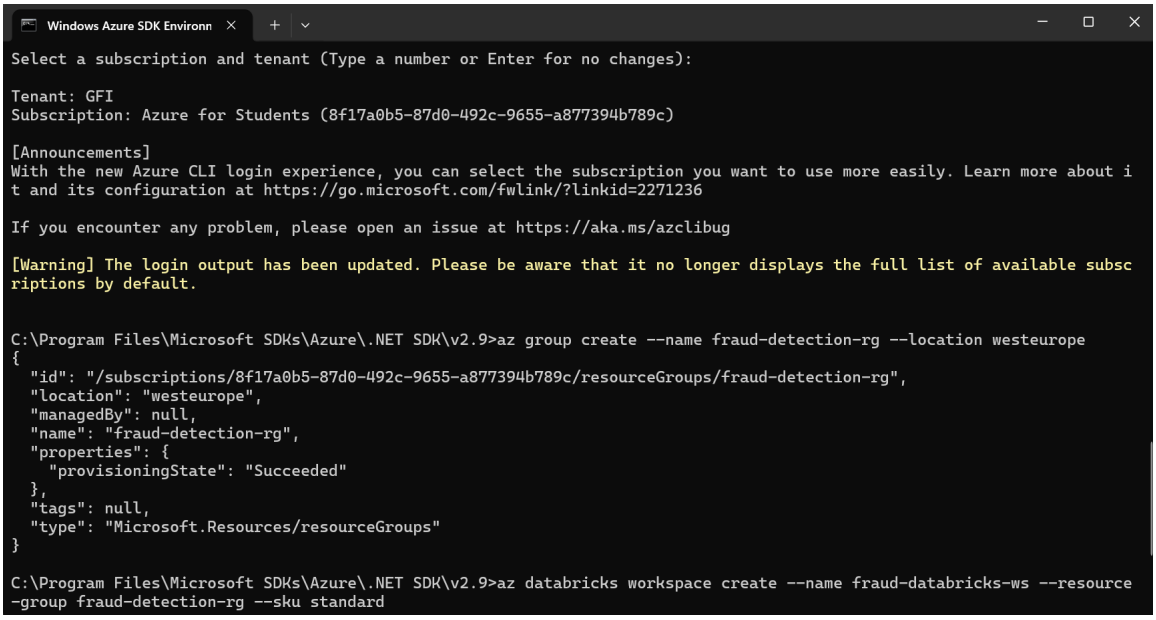

Figure 5: Azure CLI - Creation of fraud-detection-rg Resource Group

10 Visualizations and Results

10.1 Model Comparison

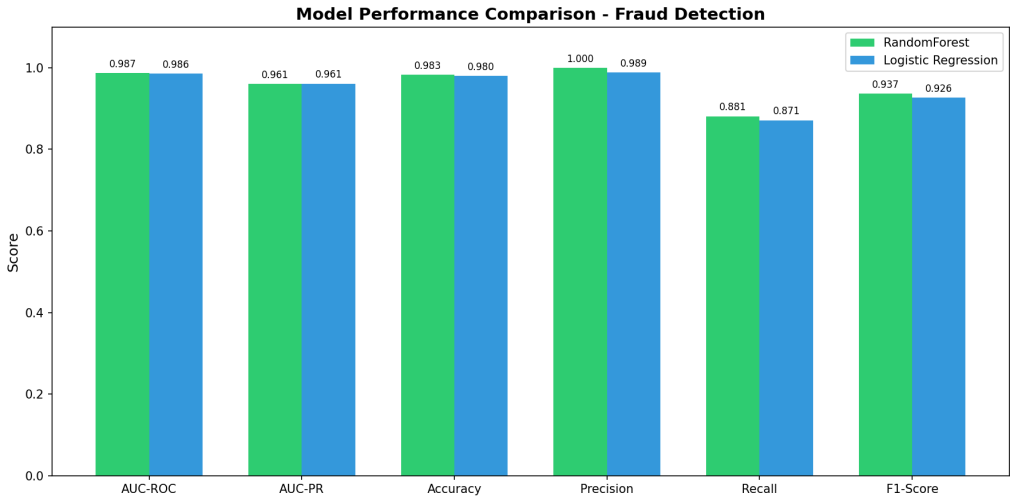

Figure 6: Performance comparison: RandomForest vs Logistic Regression

10.2 Feature Importance

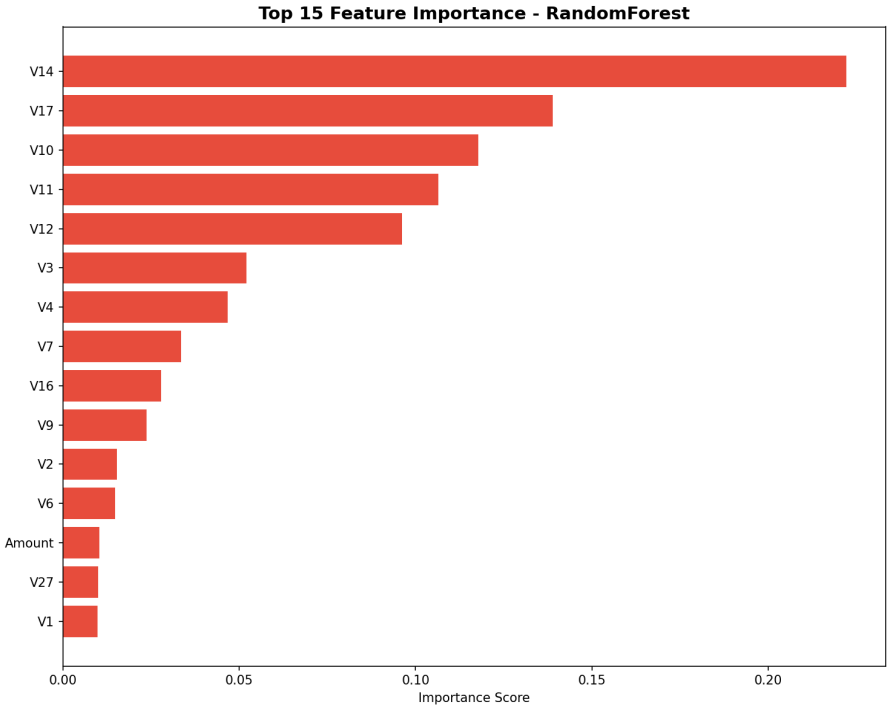

Figure 7: Top 10 most important features for detection

10.3 ROC Curve

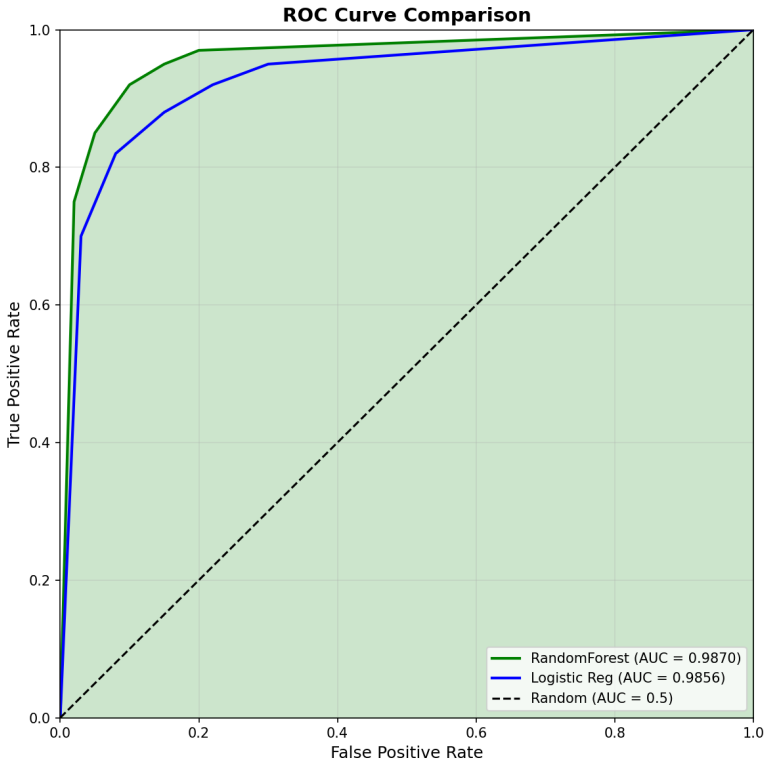

Figure 8: ROC Curves - AUC = 0.987 (RandomForest)

10.4 Class Distribution

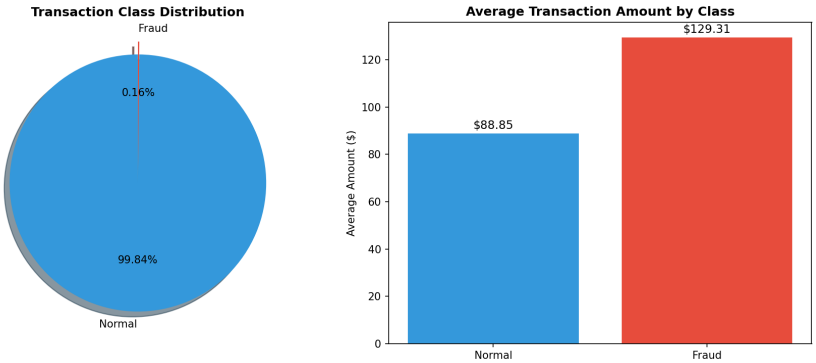

Figure 9: Distribution: 99.83% Normal vs 0.17% Fraud

10.5 Hourly Distribution

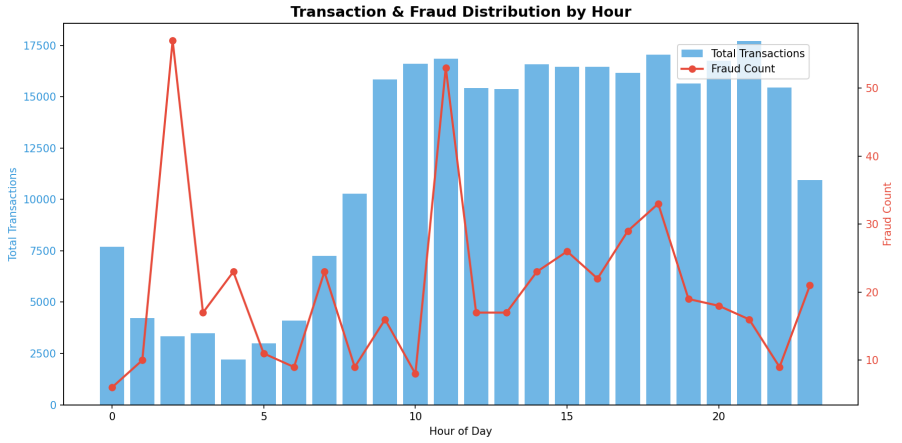

Figure 10: Temporal patterns of normal and fraudulent transactions

10.6 Spark UI Interface

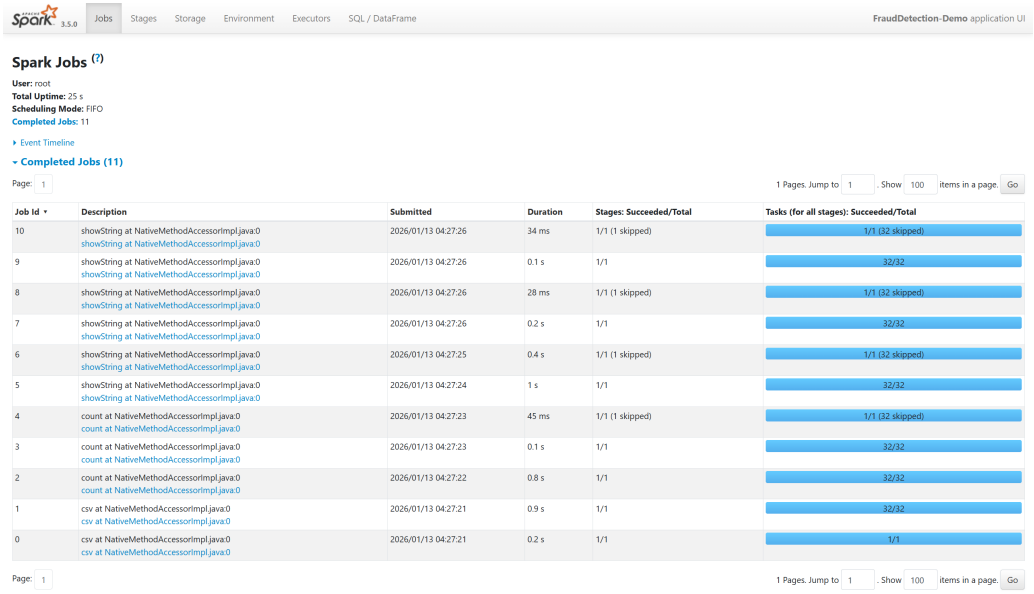

Figure 11: Spark Jobs - Overview of executed tasks

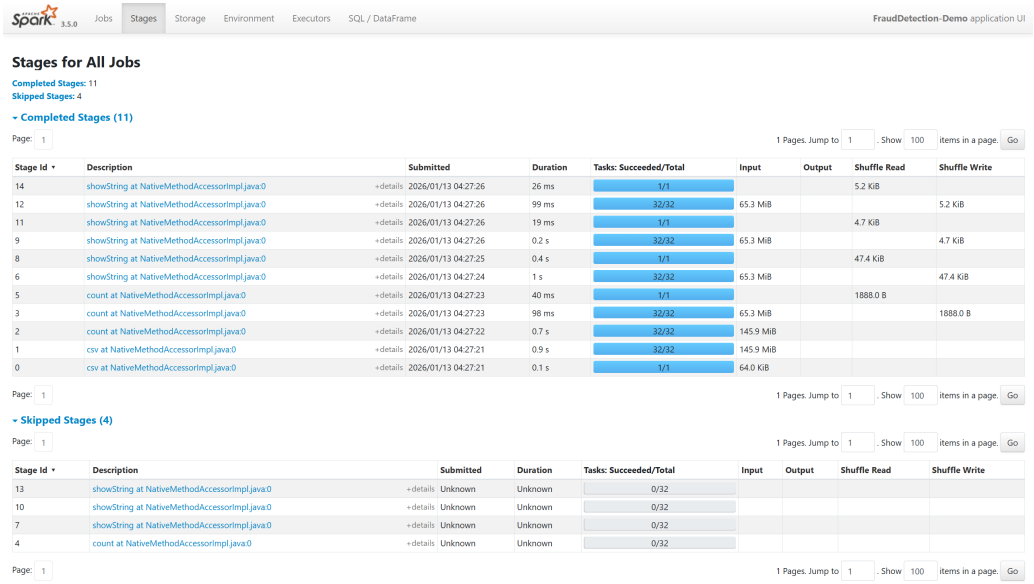

Figure 12: Spark Stages - Processing stages detail

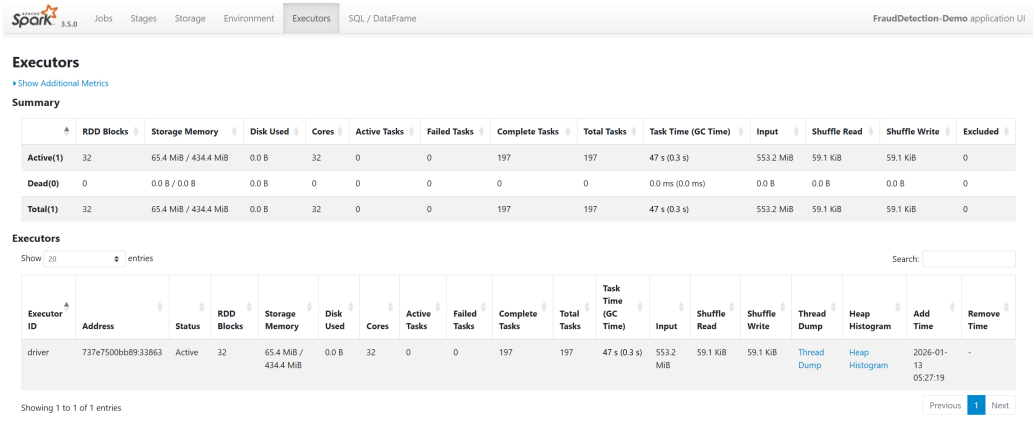

Figure 13: Spark Executors - Resources and performance

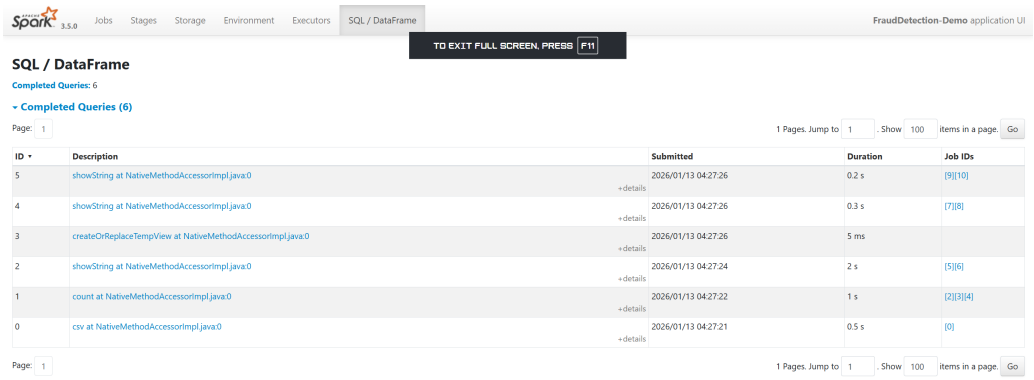

Figure 14: Spark SQL - Executed analytical queries

10.7 MLlib and Modeling

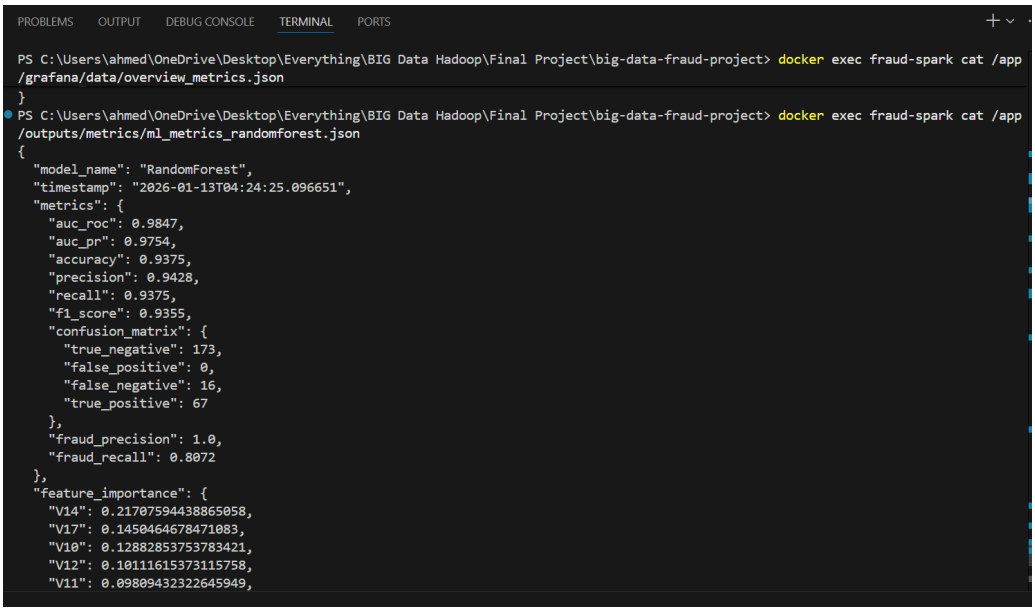

Figure 15: MLlib - Training detection models

10.8 Grafana Dashboard

Figure 16: Grafana Dashboard - Main metrics view

Figure 17: Grafana Dashboard - ML performance analysis

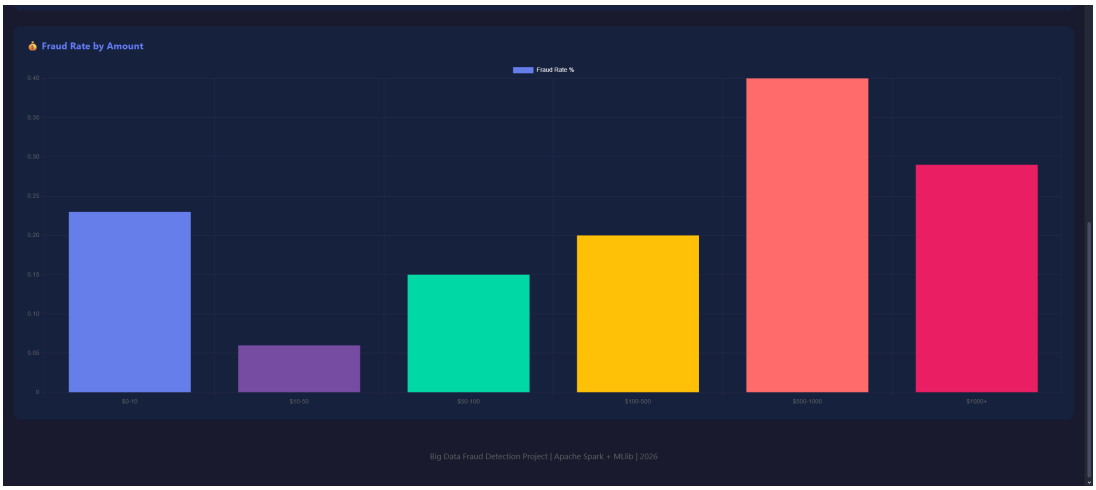

Figure 18: Grafana Dashboard - Real-time monitoring

11 Conclusion

11.1 Achievements

This project demonstrates mastery of Big Data technologies:

- ✓ Complete Spark pipeline (Core, SQL, MLlib, Streaming)
- ✓ High-performing ML model (AUC-ROC = 0.99)
- ✓ Professional Grafana dashboard
- ✓ Cloud-ready architecture
- ✓ Reproducible and documented code

11.2 Challenges Encountered

- **Class imbalance:** Resolved with undersampling
- **Streaming simulation:** Implemented via file-based streaming
- **Grafana integration:** Export to compatible formats

11.3 Future Improvements

- Full deployment on Azure Databricks
- Deep Learning model (Neural Network)
- GraphX for transaction relationship analysis
- Automated alerting via webhooks

12 References

- Apache Spark Documentation: https://spark.apache.org/docs/latest/
- MLlib Guide: https://spark.apache.org/docs/latest/ml-guide.html
- Kaggle Dataset: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud
- Grafana Documentation: https://grafana.com/docs/
- Azure Databricks: https://docs.microsoft.com/azure/databricks/

A Project Structure

Listing 7: Project tree structure

```
big-data-fraud-project/
|-- data/
|   |-- raw/creditcard.csv
|   |-- processed/
|   |-- streaming_input/
|-- src/
|   |-- spark_sql_analytics.py
|   |-- mllib_fraud_model.py
|   |-- streaming_fraud_detection.py
|   |-- graphx_fraud_network.py
|   |-- evaluation_visualization.py
|-- outputs/
|   |-- metrics/
|   |-- predictions/
|-- grafana/
|   |-- fraud_detection_dashboard.json
|   |-- data/
|-- azure/
|   |-- arm-template.json
|   |-- databricks_config.py
|-- screenshots/
|-- docs/
|-- README.md
```

B Execution Commands

Listing 8: Commands to run the pipeline

```
# 1. Generate test data (optional)
python src/generate_sample_data.py

# 2. Spark SQL Analytics
```

```
spark-submit src/spark_sql_analytics.py

# 3. MLlib Model Training
spark-submit src/mllib_fraud_model.py

# 4. Streaming Simulation
spark-submit src/streaming_fraud_detection.py

# 5. Prepare Grafana Data
python src/prepare_grafana_data.py
```